

A Conceptual Space Architecture for Widely Heterogeneous Robotic Systems¹

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Abstract. This paper describes the value of the conceptual space approach for use in teams of robots that have radically different sensory capabilities. The formal underpinnings and perceptual processes are described in the context of a biohazard detection task,

Keywords. Conceptual space, heterogeneous robot, knowledge representation

Introduction

In robotics, one of the more challenging areas is sharing knowledge across widely disparate robotic platforms. The main reason why heterogeneous robots need to share their knowledge with each other is to achieve a teamed task efficiently. Since, in this case, each robot is equipped with radically different sensors, a framework to share sensor data with other robots and efficiently represent them is essential. However, classical knowledge representations (e.g., symbolic representation and connectionist) have several deficits such as the frame and symbol grounding problems, and difficulty in computing similarity between concepts.

In order to address these problems, we use the conceptual space that Gärdenfors [1] suggested. The conceptual space is a metric world in which objects and abstract concepts are represented by quality dimensions. The concept has several domains to distinguish it from other concepts. Thus, a specific concept forms a set of regions from the domains in the conceptual space. Each domain is composed of sensor-derived quality dimensions, and the primary function of the domain is to represent various qualities of situations or objects. As a result, the linkage between a concept and domains allows the conceptual space avoid the symbol-grounding problem. Because the quality dimension is a metric world, the similarity, which is quite important in learning and induction, can be measured easily. To deal with potential sensor and representation differences, we abstract raw sensory data into natural object properties such as color, features, chemical composition, and so on. In addition, in conceptual spaces, properties of the concept are regions in a domain. The regions can represent all samples of a concept. To represent the regions of a property, we use a Gaussian Mixture Model because a property of a concept cannot be represented by one Gaussian

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in some cases. Also, we introduce a decision making process based on the conceptual space.

Earlier research in our laboratory [2-4] focused on limited heterogeneity in the sensors between robots. In our ongoing research as part of the Army Research Laboratory's Microautonomous Systems Technology Collaborative Technology Alliance, we are extending this previous work to incorporate sensor, power, communication, and computation impoverished micro-platforms with the goal of being able to provide fully distributed team coordinated control for search and rescue, biohazard detection, and other related missions [5].

1. Overview of Conceptual Spaces

The conceptual space that Gärdenfors [1] suggested is a metric world in which objects and abstract concepts are represented by quality dimensions. A specific concept is a set of regions from the domains within the conceptual space. Each domain is composed of quality dimensions, and the primary function of the domain is to represent various qualities of situations or objects.

The quality dimensions are qualities which can be acquired from sensors. Examples of qualities are temperature, shape, taste, and so on. Qualities cannot only be explicit features of objects but also abstract non-sensory characters such as fatigue and joy. A concept may also contain salience weights for properties and correlations between the properties. For some concepts, a property can be more important than others, and this can be influenced by task context. For example, let's look into how to represent the apple in the conceptual space. The apple is a concept and has diverse properties such as taste, color, shape. Each property can be mapped into one domain composed with quality dimensions. As figure 1 illustrates, the color domain of the apple has three quality dimensions: R, G, and B.

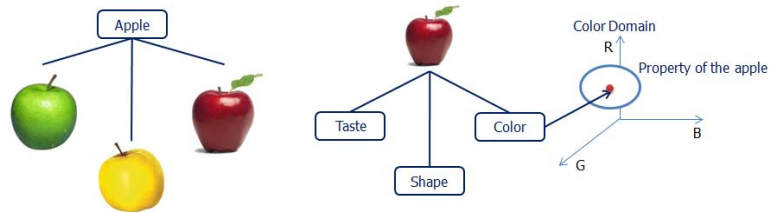


Figure 1. Properties of the apple

The varieties of apples are many, so the properties of the apple are represented as a region of a domain. For instance, if a robot detects the color of an apple and shape using a camera, sensor data from the camera is represented as a point within the quality dimensions and it can be decided whether or not the point is an apple by checking if the region of properties of the apple includes the point or by measuring the distance between the point and the prototype concept of the apple.

Consequently, the theory of conceptual spaces can yield a solution to the symbol-grounding problem that traditional methods of knowledge representation suffer from. Moreover, the conceptual space representation provides a natural way of representing similarities, and this ability is one of its major advantages.

1.1. Conceptual Space Definition

A conceptual space is defined as C . The conceptual space is composed of a symbol space S_S and a concept space C_S [6]. In the symbol space, several symbols can be defined, and each symbol names a concept. An i th concept is denoted by c_i . A concept has properties that are defined as $c(i) = c(P_1, P_2, \dots, P_n)$ and each having a range $[0, 1]$. An i th property of a k th symbol is denoted by $p(k, i) = P_{k,i}$. A set of concepts $\{c(i), i = 1, \dots, N\}$ is covered by S_S . Note that concepts are regions in conceptual space, but properties are regions in domains. A domain is represented as D_i , and the concept space, C_S is composed of domains. For instance, we can define the concept of a biohazard, (which is used in the test scenarios we are developing) as $c(1) = c(P_{1,1}, P_{1,2})$, and $P_{1,1}$ is in the color domain D_1 , and $P_{1,2}$ is in the temperature domain D_2 . Perceptual features are projected to each domain as shown in figure 2.

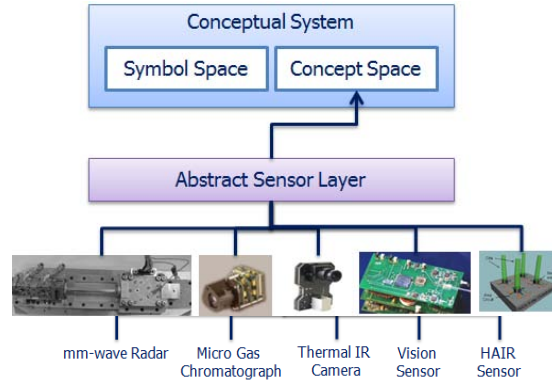


Figure 2. Schematic of conceptual space and abstract sensor layer

A prototype is the centroid of a property and serves as the most representative value of a property. Moreover, since we can categorize a sensed object by finding the closest prototype to the object, it is useful in categorization. We define the prototypical value as $f(k, j)$ in the domain D_j of the labeled with a k th symbol. Figure 3 describes the prototype of the biohazard in several domains.

Not all qualities are equally important to a concept, so we need to define the relative importance between properties. The importance of P_i in domain $D_{j(i)}$ to concept c_k is referred as $\alpha(k, j(i))$. For instance, chemical composition is a primary property in detecting a chemical weapon, since these objects have unique chemical compositions. Thus, the property must have significantly higher importance than others. As figure 3 illustrates, the chemical composition domain D_2 has much less overlap than the other domains D_1, D_3 . Therefore, the chemical domain is the most informative in discriminating the biohazard from the trash can.

1.2. Similarity in Conceptual Space

As objects can be represented as property vectors in conceptual spaces, the definition of similarity of objects is relatively intuitive and easy. The similarity [1] [6] is the distance between objects (and prototypes) and it is one of the main advantages of

this representation. Like distance, similarity is a real valued non-negative function and has several properties: The similarity should be maximum when distance is zero and decrease with distance and be zero when computing the similarity with inapplicable point. So, we define the similarity (s) between objects a and b with the following equation:

$$s(a, b) = (1 + d(a, b))^{-1}.$$

As a result, a concept (c) in the symbol space can be computed with the following equation:

$$c(k) = \sum_{i=1}^n \alpha(k, i) \cdot s(p(k, i), f(k, i)).$$

$s(p(k, i), f(k, i))$ is the similarity between an i th prototype and the i th property in a k th concept. $\alpha(k, i)$ is the importance of the i th property in the k th domain. n is the number of properties in a concept. For instance, one microrobot robot detects the color of an object, and the color domain is updated. In order to calculate the concept of the biohazard, $c(1)$, the temperature, D_1 , the chemical composition, D_2 , and the color, D_3 are required.

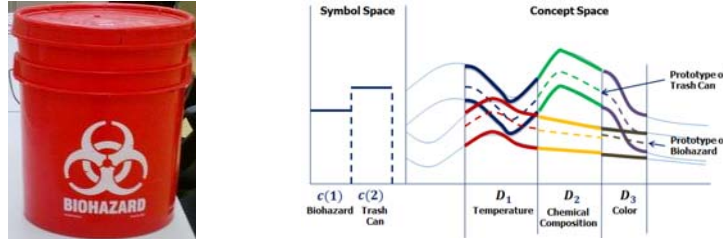


Figure 3. (Left) Potential Biohazard Object (Right) Notation for prototypes. (Adapted from [6]). Note that a similarly shaped and colored trashcan may be indistinguishable, but the chemical composition, which has no overlap provides the basis for disambiguation.

1.3. Abstract Sensor Layer

In this section, the process to convert sensor data to vectors which can represent a property of an object is described, in this case, a bio-weapon. Each robot has a set of m disjoint sensors, $S = \{s_1, s_2, \dots, s_m\}$. We denote the number of sensors as $|S|$. At time t , the robot receives an observation vector $o_{t,i}$ from each sensor, s_i , resulting in a set of measurement or observation vectors, $O = \{o_{t,1}, o_{t,2}, \dots, o_{t,|S|}\}$. We denote the robots with a superscript, so that s_i^j is sensor i of robot j . Sensor data provide a stream of unprocessed information so it is presumed that each robot has a set of p feature detectors, $F = \{f_1, f_2, \dots, f_p\}$, that further process observations and output perceptual features. We denote specific values of a set of features at time, t as F_t , and the specific value of a feature i as $f_{t,i}$. A feature detector is a function, φ , that maps a set of observation vectors into a set of feature vectors. For instance, $f_i = \varphi(o_{f_i})$ where $o_{f_i} \in O$ denotes the set of input observations used by the feature detector.

Figure 4 (left) depicts sensors, observations, and perceptual features for a robotic flyer tasked for this mission. The robot has three sensors, $S^F = \{s_1^F, s_2^F, s_3^F\}$: mm-wave radar, micro gas chromatograph, vision sensor, and thermal IR camera. A thermal IR camera provides a color image that each pixel stands for a temperature, and a blob

detector takes a thermal image as input and outputs a vector specifying a list of blobs found and their positions. After calculating an average RGB color of the output regions of the blob detector in a thermal image, temperature can be found based on a table lookup. Therefore, the feature detector, $\phi_{t,2}^F$, contains the whole process to get temperature from a thermal image.

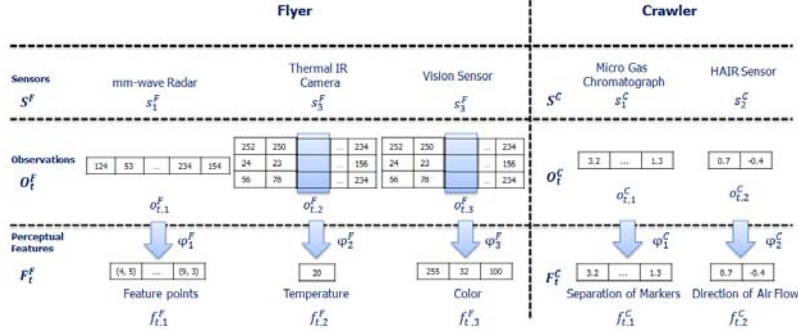


Figure 4. (Left) Flyer robot (Right) Crawler robot

The feature detector, $\phi_{t,1}^F$, for a mm-wave radar differs from $\phi_{t,2}^F$ because we need to extract features of a shape from a radar image. Instead of using the blob detector, we will use the line approximation to represent shapes in a radar image. Therefore, the feature, $f_{t,1}^F$, is composed with feature points of a recognized shape so that we can measure Euclidean distance between a detected feature and a prototype of a barrel shape. The feature detector, $\phi_{t,3}^F$, for a vision sensor is to extract blobs from an image, and then returns an average RGB color of a blob as a feature as Figure 6 (b) illustrates.

According to the scenario, the crawler has a micro gas chromatograph and a HAIR sensor, and Figure 4 (right) describes the feature detector of a crawler. Since raw sensor data of the micro gas chromatograph can be used in measuring Euclidean distance, the feature detector, $\phi_{t,1}^C$ is a null function, but $\phi_{t,2}^C$ will not be used in a property in the conceptual space since direction of air flow cannot be a property of an object. However, it can be combined with the sensor data of the micro gas chromatograph for a robot to move to the source of a biohazard using chemotaxis.

1.4. Learning Properties from Samples

In conceptual spaces, properties of the concept are regions in a domain. The regions can represent all samples of a concept. To represent the regions of a property, a Gaussian Mixture Model (GMM) [9] is used because a property of a concept cannot be represented by one Gaussian in some cases. For example, the color of an apple has several values (e.g. yellow, red, green), so representing the color with one Gaussian is not efficient.

The GMM is a parametric probability density function represented as a weighted sum of Gaussian component densities:

$$p(x|\theta) = \sum_{i=1}^M w_i \cdot p(x|\mu_i, \Sigma_i)$$

where x is feature vector for a property, and M is the number of Gaussian density functions. w_i is known as the mixing proportions,

$$0 \leq w_i \leq 1, \sum_{i=1}^M w_i = 1.$$

θ is a set containing all of the mixing proportions and model parameters,

$$\theta = \{w_i, \mu_i, \Sigma_i\}_{i=1}^M.$$

$p(x|\mu_i, \Sigma_i), i = 1, \dots, M$, are the component Gaussian densities,

$$p(x|\mu_i, \Sigma_i) = \frac{1}{\sqrt{(2\pi)^d \Sigma_i}} \exp\left(-\frac{1}{2}(x - \mu_i)^T \Sigma_i^{-1}(x - \mu_i)\right).$$

Since each property is modeled as a mixture of Gaussians, a data association problem must be solved. There will be several clusters in the space, and the algorithm must first determine which cluster the data belongs to before updating the parameters of the model. The method used to solve this is Expectation Maximization, which alternates between estimating the association of the points to the clusters and updating the parameters of the clusters given the association.

2. Summary

We have presented the underpinnings of an overall robotic architecture being developed for use in sharing knowledge across heavily constrained microautonomous platforms with respect to power, communication, sensing, and computation. The target system architecture is illustrated in Figure 5.



Figure 5: Overall System

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